Smart Structures and Systems, *Vol. 29, No. 2 (2022) 361-374*
https://doi.org/10.12989/sss.2022.29.2.361

Capturing research trends in structural health monitoring using bibliometric analysis

Jaesun Yeom [1a†], Seunghoo Jeong [2b†], Han-Gyun Woo[**1] and Sung-Han Sim[*3]

[1] *School of Business Administration, Ulsan National Institute of Science and Technology (UNIST), Ulsan 44919, Republic of Korea*
[2] *Advanced Railroad Civil Engineering Division, Korea Railroad Research Institute, Uiwang 16105, Republic of Korea*
[3] *School of Civil, Architectural Engineering, and Landscape Architecture, Sungkyunkwan University, Suwon 16419, Republic of Korea*

(*Received June 19, 2021, Revised November 11, 2021, Accepted November 12, 2021*)

Abstract. As civil infrastructure has continued to age worldwide, its structural integrity has been threatened owing to material deteriorations and continual loadings from the external environment. Structural Health Monitoring (SHM) has emerged as a cost-efficient method for ensuring structural safety and durability. As SHM research has gradually addressed an increasing number of structure-related problems, it has become difficult to understand the changing research topic trends. Although previous review papers have analyzed research trends on specific SHM topics, these studies have faced challenges in providing (1) consistent insights regarding macroscopic SHM research trends, (2) empirical evidence for research topic changes in overall SHM fields, and (3) methodological validations for the insights. To overcome these challenges, this study proposes a framework tailored to capturing the trends of research topics in SHM through a bibliometric and network analysis. The framework is applied to track SHM research topics over 15 years by identifying both quantitative and relational changes in the author keywords provided from representative SHM journals. The results of this study confirm that overall SHM research has become diversified and multi-disciplinary. Especially, the rapidly growing research topics are tightly related to applying machine learning and computer vision techniques to solve SHM-related issues. In addition, the research topic network indicates that damage detection and vibration control have been both steadily and actively studied in SHM research.

Keywords: bibliometric analysis; centrality index; network analysis; research trend; structural health monitoring

1. Introduction

Structural Health Monitoring (SHM) has received considerable attention as a promising method for monitoring structural safety and durability (An *et al*. 2019, Fujino *et al*. 2019, Kim *et al*. 2016a, b, Spencer *et al*. 2019, Ye *et al*. 2019, Hou and Xia 2020, Azimi *et al*. 2020). According to a 2017 Infrastructure Report Card by the American Society of Civil Engineers, the number of deteriorated bridges reached over 56,000 in 2016, requiring 123 billion USD for maintenance (Spencer *et al*. 2019). As a cost-effective measure for maintaining such aging structures, SHM systems have been implemented in various real-world structures by employing data acquisition, signal processing, and health diagnosis approaches (An *et al*. 2019, Fujino *et al*. 2019, Kim *et al*. 2016a, b, Spencer *et al*. 2019, Ye *et al*. 2019, Hou and Xia 2020, Azimi *et al*. 2020). Recently, advanced sensing devices have enabled the development of SHM-related technologies for assessing the in-service conditions of civil infrastructure elements (An *et al*. 2019, Fujino *et al*. 2019, Kim *et al*. 2016a, b, Spencer *et al*. 2019, Ye *et al*. 2019, Hou and Xia 2020, Azimi *et al*. 2020). With the progress in SHM technologies, SHM research has become increasingly diversified in terms of its topics, including damage detection, condition assessment, system identification, modal analysis, vision-based displacement measurement, and infrastructure maintenance (An *et al*. 2019, Fujino *et al*. 2019, Kim *et al*. 2015, 2016a, b, 2019, Spencer *et al*. 2019, Ye *et al*. 2019, Hou and Xia 2020, Azimi *et al*. 2020, Jeong *et al*. 2019, Sim 2016, Moreu *et al*. 2016, Lee *et al*. 2012, 2019, 2020a, Lee *et al*. 2016, Park *et al*. 2016, Fukuda *et al*. 2010, Lee and Shinozuka 2006).

As the SHM field has become complicated, researchers have faced difficulties in tracking the emerging research topics. Extensive literature reviews have been conducted worldwide to understand the historical development of SHM research trends (An *et al*. 2019, Fujino *et al*. 2019, Kim *et al*. 2016a, b, Spencer *et al*. 2019, Ye *et al*. 2019, Hou and Xia 2020, Azimi *et al*. 2020). These review studies have focused on specific SHM topics in detail, such as damage detection (An *et al*. 2019, Hou and Xia 2020), sensor technologies (Kim *et al*. 2016a, b), computer vision-based SHM (Spencer *et al*. 2019), SHM systems (Fujino *et al*. 2019), and deep learning-based SHM (Ye *et al*. 2019, Hou and Xia 2020, Azimi *et al*. 2020), based on limited

*Corresponding author, Ph.D., Professor,
E-mail: ssim@skku.edu
**Co-corresponding author, Ph.D., Associate Professor,
E-mail: hwoo@unist.ac.kr
[a] Ph.D. Student
[b] Ph.D., Senior Researcher
[†] These authors contributed equally to this work as first authors

ISSN: 1738-1584 (Print), 1738-1991 (Online)

numbers of papers selected by the authors' judgement. However, previous reviews have several limitations in identifying the historical changes and current issues in the field of SHM. First, the authors' subjective opinions may cause inconsistent interpretations of macroscopic research trends (Lee 2012, Schlederer *et al*. 2014, Oraee *et al*. 2017). As few frameworks for capturing research trends exist in the SHM field, previous studies inevitably depend on the authors' expertise, which may lead to different opinions in interpreting the research trends. Second, the previous reviews consider a limited number of papers, and thus may provide weaker empirical evidence of topic changes. Third, as previous studies have manually reviewed the literature to identify research trends, replicating the review process is laborious and time-consuming, especially if the number of publications has dramatically increased (Oraee *et al*. 2017). Thus, a data-driven approach is needed for identifying research trends to guarantee the methodological validity and reduce the costs simultaneously.

As an effort to capture research trends, bibliometric analyses have been widely adopted in various research fields (Oraee *et al*. 2017, Ye *et al*. 2013, Kim *et al*. 2016a, b, 2021, Zhai *et al*. 2015, Demiroz and Hasse 2019, Rosas *et al*. 2011, Uddin *et al*. 2012, Uysal 2010, Woo *et al*. 2013, Hong *et al*. 2012, Ke *et al*. 2009, Abudayyeh *et al*. 2004, Khan *et al*. 2016). A bibliometric analysis is a widely used technique for evaluating bibliographic data from scientific papers, such as the title, abstract, and keywords, regarding the quantitative and relational aspects of the subject matter. This method has shown potential for addressing the problems in prior SHM reviews. First, the bibliometric analysis provides objective evidence (i.e., bibliographic data) to scholars to identify the research topic changes, thereby increasing the level of consistency in interpretation. Second, this method can save time and labor forces, as it examines considerable range of scientific publications by searching through all related papers from an online database containing a variety of international journals. Third, it is possible to analyze the co-occurrences of research topics in publications by applying a network analysis. Network analyses are widely adopted in bibliometric analyses to visualize the relationships among members (e.g., topics) by drawing the networks graphically.

Accordingly, this study aims to propose a new framework for analyzing the research topic trends in SHM studies using a bibliometric analysis. The research trends are interpreted according to two aspects, i.e., the quantitative and relational changes in the SHM-related topics, to deeply examine the development history of the SHM field. Our framework is designed to collect bibliographic data from a publication database and then construct topic networks. The networks enable us to examine which topics are interrelated over time so that scholars can observe dynamic patterns of research trends in SHM communities. Based on descriptive statistics and network indices, the proposed framework helps researchers understand the SHM field in terms of the quantitative and relational changes in its research topics. This study collected SHM-related publications for 15 years from representative journals to apply the proposed framework. The results of this study provide objective evidence of the macroscopic changes in research topics, in terms of both their quantitative and relational aspects.

2. Bibliometric analysis

A bibliometric analysis is an efficient data-driven approach used to enable a comprehensive understanding of complex and multidisciplinary research fields (Oraee *et al*. 2017, Ye *et al*. 2013, Kim *et al*. 2016a, b, 2021, Zhai *et al*. 2015, Demiroz and Hasse 2019, Rosas *et al*. 2011, Uddin *et al*. 2012, Uysal 2010, Woo *et al*. 2013, Hong *et al*. 2012, Ke *et al*. 2009, Abudayyeh *et al*. 2004, Khan *et al*. 2016). This approach involves a quantitative assessment of the bibliographic metadata contained in each publication, such as the title, abstract, keywords, references, publication date and, number of citations. The primary assumption is that scientific publication is one of the fundamental driving forces in the advancement of science, as it fosters knowledge distribution (Rosas *et al*. 2011). For example, the keywords in scientific articles reflect the critical concepts in the articles and research methods used (Zhai *et al*. 2015, Rosas *et al*. 2011). Hence, a bibliometric analysis provides scholars with the objective data contained in each paper, inspiring a systematic review of the research trends.

A network analysis is an advantageous bibliometric method for examining members' relationship structures (e.g., keywords). Various academic fields such as biomedicine, ocean engineering, transportation, disaster management, and tourism have utilized such analyses to understand their research trends (Oraee *et al*. 2017, Ye *et al*. 2013, Kim *et al*. 2016a, b, 2021, Zhai *et al*. 2015, Demiroz and Hasse 2019, Rosas *et al*. 2011, Uddin *et al*. 2012, Uysal 2010, Woo *et al*. 2013). This study introduces the network perspective, as expressed by the topic networks, to analyze the research topic changes (i.e., which research topics have been studied together).

2.1 Network representations

A network can be described by two components: a node and a link, as shown in Fig. 1. A node represents a member in the network, such as a topic, and is represented by a point. A link connects two interrelated nodes using a line, with two types of directions: directed and undirected. A directed connection is used when two nodes have flows or directions. An undirected connection is used to present a connection state between two nodes without flows or directions (i.e., the path from node i to node j is identical to

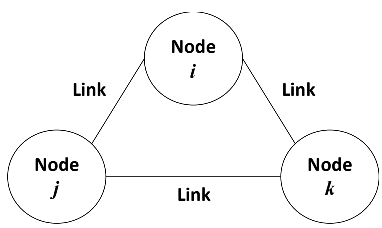


Fig. 1 Components constituting the network

the path from node *j* to node *i*).

A network can be represented by a matrix denoted as, for example, adjacency matrix A, which is an $n \times n$ symmetric matrix, where n is the number of nodes in the network. The adjacency matrix is defined as shown in Eq. (1).

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge between nodes } i \text{ and } j \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

In the above, $A_{ij} = 1$ indicates that nodes i and j are connected. If nodes i and j are unconnected, the value of A_{ij} is equal to 0.

2.2 Network centralities

A centrality index helps to identify which nodes play essential roles in the entire network (Kim *et al.* 2017, Freeman *et al.* 1979, Borgatti 2005). Several types of centrality measures are generally adopted to assess the topological significance of nodes, such as degree centrality, betweenness centrality, and eigenvector centrality. Each centrality index has a different perspective for evaluating the importance of nodes. First, degree centrality is an efficient approach to identifying significant nodes, based on the number of links that the nodes have. The degree centrality of node i for a given graph $G ≔ (V, E)$ with $|V|$ nodes and $|E|$ links can be defined as shown in Eq. (2), where n is the number of nodes.

$$C_D(i) = \frac{1}{n-1}\sum_{j=1}^{n} A_{ij} \quad (2)$$

Second, the betweenness centrality calculates the significance of a node i based on the share of times when node i is necessary for node j to reach node k via the shortest path. The centrality of node i in a graph $G ≔ (V, E)$ is computed using Eq. (3).

$$C_B(i) = \sum_{x \neq i \neq y \in V} \frac{\sigma_{xy}(i)}{\sigma_{xy}} \quad (3)$$

Here, σ_{xy} is the total number of shortest paths from node x to node y, and $\sigma_{xy}(i)$ is the number of paths passing through node i. A node with a high value for this measure represents an important node for spreading information through the network. Third, eigenvector centrality is used to weigh important nodes using an eigenvector score. The relative centrality score x of a node i can be calculated as follows

$$x_i = \frac{1}{\lambda}\sum_{j=1}^{n} A_{ij} x_j \quad (4)$$

Here, λ is a constant. Assuming a vector of relative centralities $X = (x_1, x_2, x_3, \ldots x_n)$, Eq. (4) can be reformulated into a matrix form with eigenvalues (λ) and corresponding eigenvectors (X), as follows:

$$AX = \lambda X \quad (5)$$

Among the different eigenvalues of λ, a nonzero eigenvector solution exists, satisfying Eq. (5). As the elements in the adjacency matrix are nonnegative, a unique eigenvalue can be obtained based on the Perron–Frobenius theorem. The corresponding eigenvectors of X represent the eigenvector centrality scores. The node with the highest eigenvector score is the principal node and is adjacent to other nodes with high centrality scores.

Table 1 summarizes the centrality measures used in this study. The table includes the types of centrality measures and their descriptions, followed by operational definitions (Newman 2016). Centrality measures are described in more detail in other studies (Freeman *et al.* 1979, Borgatti 2005, Newman 2016).

3. Method

This study proposes a framework for obtaining a comprehensive understanding of the research topic trends in the SHM field, as shown in Fig. 2. The proposed framework is composed of five steps: (1) journal selection, (2) data collection, (3) data preprocessing, (4) bibliometric analysis, and (5) analysis of the research trends. A more detailed explanation of each step is provided below.

3.1 Journal selection

As the SHM field is multidisciplinary and covers a wide range of research scopes, it is challenging to select suitable journals that represent the field. In this study, we considered various previous studies that attempted to provide journal selection approaches for avoiding selection bias (Palmer *et al.* 2005). First, management and tourism studies have

Table 1 Summary of centrality measures

Type of centrality	Description	Operational definition
Degree centrality	The importance of a node based on the number of links that a node has	$C_D(i) = \frac{1}{n-1}\sum_{j=1}^{n} A_{ij}$
Betweenness centrality	The number of times a node acts as a bridge along the shortest path between two other nodes	$C_B(i) = \sum_{x \neq i \neq y \in V} \frac{\sigma_{xy}(i)}{\sigma_{xy}}$
Eigenvector centrality	The influence of a node in a network based on the relative importance of adjacent nodes	$C_E(i) = x_i = \frac{1}{\lambda}\sum_{j=1}^{n} A_{ij} x_j$

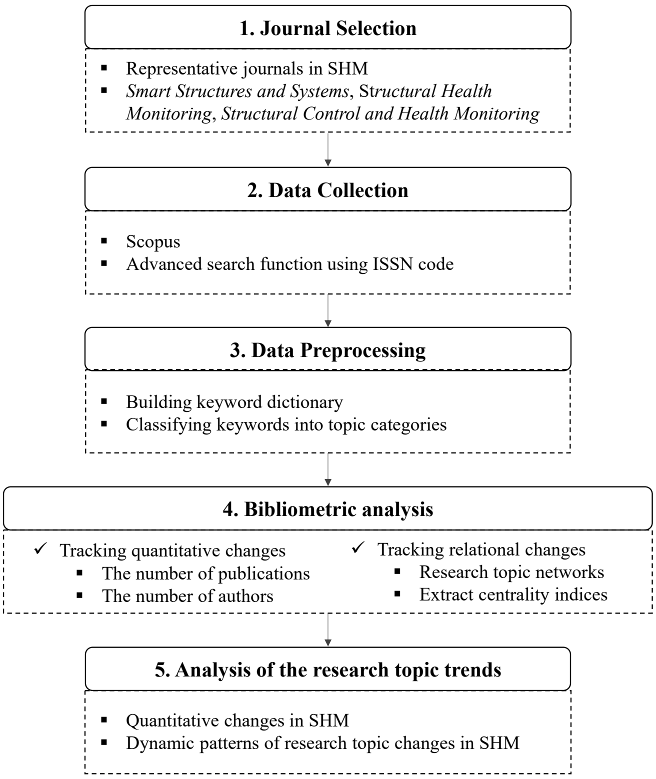


Fig. 2 Research framework for analyzing research topic trends of SHM-related studies

utilized a leading journal list, announced by a credible press source such as the Financial Times (Palmer *et al*. 2005, Ferreira *et al*. 2014). This approach is less controversial, because there is consensus on the fitness of journals in the corresponding research fields. Second, information science studies have employed the subject categories provided by the Journal Citation Reports (*JCR*). These categories enable scholars to search for appropriate journals fitting the research field boundary (Chang and Huang 2012). Third, medical and clinical studies have attempted to collect relevant journals through keyword search functions provided by web databases such as the Web of Science or Scopus (Oraee *et al*. 2017, Ugolini *et al*. 2007). The journal information can be extracted from the retrieved papers from the search results. Lastly, authors tend to select journals fitting the research field based on their subjective judgments (Abudayyeh *et al*. 2004) when: (1) the field of study covers highly multidisciplinary subjects, (2) there is little consensus on the appropriate journals within the research field, and (3) the authors have specific research interests.

This study adopted the last approach, and manually selected journals of interest. There are three reasons for this. First, the SHM field has relatively little consensus on the representative journals. Second, it is difficult to select leading SHM-related journals based on the *JCR*, because the *JCR* subject categories do not contain SHM as a research subject. Third, keyword searches from web databases can omit SHM-related papers if the authors omit SHM terms in the bibliographic metadata such as the title, abstract, and keywords. Thus, this study selected three SHM journals (i.e., *Smart Structures and Systems*, *Structural Control and Health Monitoring*, and *Structural Health Monitoring*) for the following reasons. First, the selected journals have high credibility and frequent citations by various SHM papers; therefore, researchers believe that the topic trends identified from these journals are credible. Second, these journals have enough publications, covering a wide range of SHM research from general to specific topics. Sufficient research papers ensure less bias in the overall landscape of research topics. Notably, the selection does not include all journals in which the SHM papers are published.

3.2 Data collection

This study collected bibliographic information from the Scopus website. Scopus is Elsevier's abstract and citation database; in 2019, it covered 34,346 peer-reviewed journals from 11,678 publishers. The database offers bibliographic metadata such as the keywords, author profiles, number of publications, and references. The reasons for adopting Scopus as our data source were twofold. First, the Scopus website offers publication information through advanced search functions that enable users to find raw data regarding research articles from target journals. This study used the International Standard Serial Number (ISSN) codes of the journals as the primary search parameters. Once a query with ISSN codes is entered, the website provides all registered papers from the selected journals in the database. Each research paper contains publication information such as the publication date, journal name, ISSN code, publisher name, title, abstract, keywords, references, and number of citations. Second, the Scopus website contains representative journals in the SHM field. The inclusion of the major SHM journals is essential for identifying the research topic trends in SHM studies.

3.3 Data pre-processing

After collecting bibliographic data from the SHM journals, the extracted information was transformed into an appropriate form for analysis. In this study, the collected data were processed into a machine-readable format through Python preprocessing modules such as the pandas and scikit-learn packages. These packages allowed us to eliminate grammatical ambiguity by integrating various forms of synonyms with a representative topic. The preprocessing procedure consists of three stages: (1) building a keyword dictionary based on the author keywords from each paper, (2) classifying similar keywords into each topic category, and (3) slicing the dataset according to the time frame.

The procedure began by constructing a keyword dictionary by organizing the individual keywords presented in each paper. Generally, authors usually put several keywords when they publish their papers, so that readers can obtain a sense of the contents. These keywords provide important information for understanding the overall landscape of the research theme. Specifically, the keyword dictionary consists of each keyword and the number of times this keyword appears in the '*keyword section*' of the entire set of papers. If paper A has three keywords (damper, sensor, machine learning) and paper B has three keywords (sensor, signal processing, damper), for example, the keyword dictionary would be as follows: *sensor*: *2*, *damper*: *2*, *signal processing*: *1*, *machine learning*: *1*. The dictionary allows scholars to examine the research topics that have been steadily studied, along with issues that have been recently emerged.

After building a keyword dictionary, we manually classified similar keywords into the same topic category. Here, similar keywords refer to keywords with diverse formats but identical meanings. For example, *damage detection* and *damage identification* have different characters, but they have identical meanings in terms of research topics. This study constructs the topic category by reorganizing the research subjects corresponding to the aims and scope of the three target journals. Classifying similar keywords into a single topic category can reduce the time-required to review all keywords, as well as the semantic ambiguity arising from keywords with similar meanings.

Once the topic category was finalized, the dataset was divided into multiple parts according to an appropriate time interval. The divided dataset is used to capture the changes occurring between each time frame. Here, a total of 15 years from 2005 to 2019 were considered to collect the bibliographic metadata from the selected journals, as the number of publications before 2005 was insufficient for analysis of the research topic trends. This study set three consecutive time frames within a five-year interval to understand the research topic changes in the SHM field over time. In general, the corresponding time interval can be adjusted depending on the type of the research field.

3.4 Bibliometric analysis

This study analyzed the research topic trends by tracking two aspects: the quantitative changes in emerging research topics, and the relational changes among these topics.

3.4.1 Tracking quantitative changes

This step tracked changes in the number of publications and authors, and emerging research topics. Specifically, this study monitored the yearly changes in the number of papers and authors from the three selected journals over 15 years. When calculating the number of authors, this study counted authors who publish multiple papers in a certain year as one author. For quantitative changes in research topics, this study considered five years as the time interval. Thus, this study could observe the changes in three-time frames over 15 years in total. When tracing the changes in research topics over each time frame, we counted the number of keywords classified into the same topic categories, as defined in the previous step.

3.4.2 Tracking relational changes

This step aimed to trace the relational changes in the co-studied research topics using a network analysis. The tracking process comprised two steps: (1) constructing research topic networks, and (2) extracting network centrality indices. The subsequent steps were implemented by the 'networkx' package provided by the Python programming language. This package provides various useful functions for visualizing nodes and edges.

<u>Constructing research topic networks</u>

The procedure started with the construction and visualization of the topic networks. The premise of the study is that the keywords included in a paper represent its research theme. Thus, this study could track the changes in research topics over time by quantifying the keywords. Here, the nodes were the preprocessed topic categories, and the links were the number of co-occurrences of each category. If a paper had three topic categories, such as damage detection, bridges, and machine learning, for example, the links would be three pairs of topics: damage detection–bridges, damage detection–machine learning, and bridges–machine learning. The weight of a link shows how actively scholars have studied two topics simultaneously. The more the topic combination appears, the more attention this topic combination has received.

<u>Extracting network centralities</u>

In this step, the network centrality indices were extracted from the topic networks constructed from the previous step. These centrality indices measure the importance of a node relative to all other nodes in a given network. The characteristics of each centrality index are as follows. First, the degree centrality is calculated based on the number of connections that a node has. The more relational links a node has, the higher the value of the degree centrality. Second, the betweenness centrality is based on the degree to which a specific node lies on the shortest paths between other pairs of nodes. The betweenness centrality for a node increases when many shortest paths pass this node. Finally, the eigenvector centrality is a more sophisticated version of the degree centrality. It considers not only the number of links a node has, but also the quality of the connections; thus, this score increases when a node is connected to other nodes with high centrality. The changes in centrality scores provide a hint for estimating the life cycle of each research topic.

3.5 Analysis of the research topic trends

This step analyzed the research topic trends in the SHM field. The trend included the dynamic patterns of relational changes in the research topics, as well as the overall quantitative changes in the number of publications and authors. Based on the descriptive statistics and extracted centrality indices from the previous steps, this study could examine not only the growth of the field, but also the changes in the dominant or emerging topics over time. The results of the analysis confirm the arguments from previous research topic trend literature, providing comprehensive explanations from the empirical data. The analyzed research trends are described in the following section.

4. Results

The research trends in SHM were analyzed based on the proposed research framework. Through the Scopus advanced searching engine and input ISSN code parameters, this study collected 3,315 research articles from three representative journals in the SHM field: *Smart Structures and Systems* (ISSN: 1738-1991), *Structural Control and Health Monitoring* (ISSN: 1545-2263) and *Structural Health Monitoring* (ISSN: 1741-3168). The collected dataset contained author IDs, author names, titles, keywords, publication dates, publishers, and journal names. The extracted data were transformed into an appropriate form to obtain information regarding the research topics for three time periods. After preprocessing the collected papers, a descriptive analysis was conducted to identify quantitative changes in the SHM field, including the number of publications and authors by year and major topics in SHM studies. Then, the relational changes were investigated in terms of research topics with three periods over 15 years: 2005–2009 (Period 1), 2010–2014 (Period 2), and 2015–2019 (Period 3).

4.1 Analyzing the quantitative changes

The annual number of publications from the selected journals is shown in Fig. 3. A sharp increase in the annual number of publications has been observed since 2005. For example, 22 publications are released in 2005, but the number of publications increases to 495 in 2019, that is, an increase by a multiple of 22.5.

With the increasing number of published articles, the number of authors contributing to the SHM field has also shown an increasing trend since 2005, as shown in Fig. 4. The number of authors is 1,542 in 2019, an increase of 28 times the value in 2005. Thus, this study finds that the SHM field has experienced quantitative growth based on the increasing number of publications and authors.

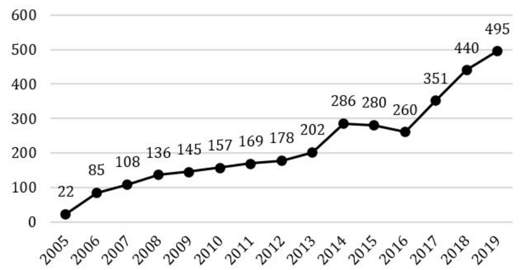


Fig. 3 Number of SHM-related publications (2005–2019)

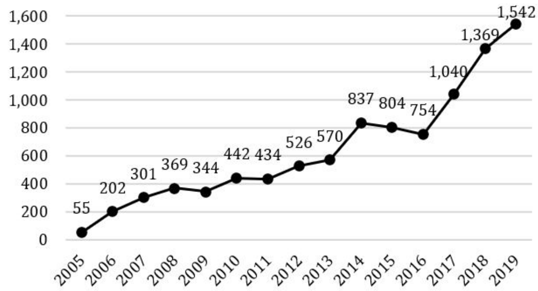


Fig. 4 Number of authors (2005–2019)

The top 20 topics appearing frequently in the three journals are summarized in Table 2. It is noted that *structural health monitoring* is excluded because this topic represents the academic field itself. The publications from each period included 1,173, 2,425, and 4,454 keywords, respectively. Similar keywords with identical meanings were classified into 70 topic categories that are built based on expert knowledge. Although vibration control may not be a sub-category in SHM studies, control-related topics are included in the constructed topic categories. This study observes frequent appearances of control-related subjects in authors' keywords from publications in the selected SHM journals. The inclusion of these topics can enable us to deeply understand the research trends in the SHM field by examining their relationships with control-related topics. As shown in Table 2, three topics, *damage detection*, *non destructive testing*, and *vibration control*, have been mentioned continually in SHM journals since 2005. Although *system identification* is ranked 4^{th} in Periods 1 and 2, the rank drops to 13^{th} in Period 3. Instead, *machine learning* appears in Period 2 for the first time, and then becomes a widely used topic, as it is ranked 8^{th} in Period 3. With the advent of *machine learning*, *computer vision* also begins to appear within the top 20 topics in Period 3. Owing to advanced SHM-related technologies, additional damage types have been considered in SHM studies. This study finds that *damage type* has been mentioned regularly; its rank increases from 14^{th} in Period 1 to 7^{th} in Period 3.

4.2 Analyzing research topic changes

This study constructs topic networks for the three periods to understand the relational changes in the research topics. Each network indicates the research topics that have

Table 2 Top 20 SHM research topics during each period

Period 1 (2005-2009)		Period 2 (2010–2014)		Period 3 (2015–2019)	
Topic	**#**	**Topic**	**#**	**Topic**	**#**
vibration control	131	damage detection	230	damage detection	858
damage detection	118	vibration control	205	non destructive testing	756
non destructive testing	72	non destructive testing	197	vibration control	473
system identification	49	system identification	86	loading	464
damper	48	loading	86	modal analysis	401
loading	44	modal analysis	84	damper	358
seismic analysis	37	sensor development	82	damage type	329
bridge	35	signal processing	81	machine learning	296
isolation system	34	damper	77	bridge	295
signal processing	33	damage type	70	signal processing	294
modal analysis	31	wireless sensor network	64	optimization	265
sensor development	30	optimization	59	seismic analysis	264
smart material	28	bridge	55	system identification	259
damage type	27	smart material	54	sensor development	250
optimization	23	seismic analysis	48	computer vision	217
finite element analysis	22	machine learning	44	data acquisition	204
building structure	20	data acquisition	35	finite element analysis	195
benchmark problem	17	finite element analysis	33	smart material	186
data acquisition	15	dynamics	32	environmental effect	166
wireless sensor network	14	nonlinear analysis	31	isolation system	164

Table 3 Centrality indices of top 15 topics in Period 1

Rank	Topic	Degree centrality	Betweenness centrality	Eigenvector centrality
1	vibration control	0.733	0.733	0.788
2	damage detection	0.333	0.543	0.051
3	non destructive testing	0.333	0.257	0.017
4	isolation system	0.133	0	0.329
5	seismic analysis	0.133	0	0.274
6	signal processing	0.133	0	0.122
7	system identification	0.133	0.457	0.113
8	damper	0.067	0	0.319
9	benchmark problem	0.067	0	0.164
10	modal analysis	0.067	0	0.009
11	damage type	0.067	0	0.003
12	loading	0.067	0	0.008
13	optimization	0.067	0	0.112
14	bridge	0.067	0	0.112
15	damping	0.067	0	0.104

been studied together within each time frame. After preprocessing the raw data, topic networks are drawn for the three periods to illustrate the co-occurrences of the topics appearing in each publication. Topics mentioned with others over eight times are graphically represented in the networks for better readability.

The topic network in Period 1 shows that *vibration control*, *damage detection*, and *non destructive testing* are the main topics, as shown in Fig. 5 and Table 3. The topic of *damage detection* is often presented with *non destructive testing*, whereas *vibration control* is less related to the other two main topics. The *damage detection* is mentioned together with *modal analysis*, *system identification*, and *non destructive testing*, i.e., representative approaches to detecting structural damage (Hou and Xia 2020). The *vibration control* mostly appears with control-related topics, including *damper*, *damping*, and *isolation system*.

The centrality indices in Table 3 show that three topics (i.e., *vibration control*, *damage detection*, and *non destructive testing*) have the first to third highest scores of degree centrality, indicating frequent co-occurrences with other topics. In the case of the betweenness centrality, *vibration control* has the highest score among the top 15 topics, that is, connecting other topics through the shortest path. In the case of eigenvector centrality, *vibration control* is ranked first, whereas *damage detection* and *non destructive testing* have relatively low scores. This result indicates that the adjacent topics connected with *damage detection* and *non destructive testing* have relatively low centrality scores.

An expansion of the topic network regarding the number of topics and links is observed in Period 2. The topic network contains 25 topics appearing more than eight times with others, i.e., greater than 16 topics in Period 1. The number of linkages also increased from 19 (Period 1) to 53 in Period 2. In this time frame, *machine learning* begins to appear in the topic network, mostly with *damage detection* and *system identification*. Furthermore, wireless sensor systems have received much attention in SHM-related studies, as can be identified by the topics of *wireless sensor network* and *sensor development*, as indicated in Fig. 6. In addition, three topics, *vibration control*, *damage detection*,

Table 4 Centrality indices of top 15 topics in Period 2

Rank	Topic	Degree centrality	Betweenness centrality	Eigenvector centrality
1	vibration control	0.625	0.48	0.715
2	damage detection	0.5	0.15	0.275
3	non destructive testing	0.458	0.263	0.325
4	isolation system	0.375	0.181	0.099
5	seismic analysis	0.333	0.085	0.224
6	signal processing	0.292	0.033	0.129
7	system identification	0.208	0.011	0.102
8	damper	0.167	0.047	0.292
9	benchmark problem	0.167	0	0.062
10	modal analysis	0.125	0.036	0.123
11	damage type	0.125	0.014	0.044
12	loading	0.125	0.009	0.076
13	optimization	0.125	0.018	0.158
14	bridge	0.125	0.067	0.17
15	damping	0.083	0.034	0.118

Table 5 Centrality indices of top 15 topics in Period 3

Rank	Topic	Degree centrality	Betweenness centrality	Eigenvector centrality
1	damage detection	0.697	0.364	0.5
2	non destructive testing	0.455	0.164	0.486
3	vibration control	0.455	0.263	0.359
4	damper	0.273	0.045	0.26
5	modal analysis	0.273	0.011	0.198
6	loading	0.273	0.076	0.245
7	machine learning	0.273	0.073	0.219
8	signal processing	0.242	0.011	0.187
9	optimization	0.242	0.103	0.108
10	bridge	0.212	0.07	0.125
11	computer vision	0.212	0.069	0.088
12	system identification	0.212	0.075	0.108
13	damage type	0.182	0.019	0.186
14	seismic analysis	0.152	0.021	0.101
15	model updating	0.091	0.008	0.069

and *non destructive testing*, still maintain the dominant positions in the network. Along with the three dominant topics, the *system identification* and *loading* function as significant nodes for connecting other topics.

Based on the centrality indices in Table 4, three topics, *vibration control*, *damage detection*, and *non destructive testing*, account for a large portion of the number of co-occurrences with other topics. In the case of the betweenness centrality, *vibration control* and *non destructive testing* are essential topics for connecting other pairs via the shortest path. The eigenvector centrality shows that *vibration control* has the highest score, followed by *non destructive testing*, *damper*, and *damage detection*.

The topic network in Period 3 becomes more complicated than that in Period 2, as shown in Fig. 7. There are 34 topics, i.e., the topic network in Period 3 is larger than the 25 topics in Period 2. The number of links also increases from 53 in Period 2 to 87 in Period 3. Three topics, *damage detection*, *non destructive testing*, and *vibration control*, remain significant. High co-occurrences are observed between *damage detection* and *non destructive testing*. The *vibration control* is strongly connected with control-related topics but has weaker linkages with the other two dominant topics. The emergence of *computer vision* is observed for the first time, connected to *machine learning*, *displacement measurement*, and *non destructive testing*. The *machine learning* remains an important topics in the network, having connections with *damage detection*, *non destructive testing*, *modal analysis*, and *computer vision*.

In Period 3, three dominant topics in the previous period remain placed at the first to third ranks, respectively, in terms of the three centrality indices, as shown in Table 5. The *damage detection* has the highest scores for the three centrality indices. The *vibration control* has fewer connections with the two major topics, and thus has a relatively low eigenvector centrality score of 0.359. As *vibration control* is a significant topic functioning as a bridge for connecting other control-related topics, this topic has the second-highest scores in terms of the degree and betweenness centrality. The *non destructive testing* is closely related to *damage detection*, and thus has the second rank in the degree and eigenvector centrality indices.

5. Discussion of research topic trends

Although the descriptive analysis shows the quantitative changes in the SHM research topics, it is challenging to capture the development history of SHM fields, e.g., which topics have been studied together. This study performs a network analysis to provide an in-depth understanding of SHM trends in quantitative and relational aspects.

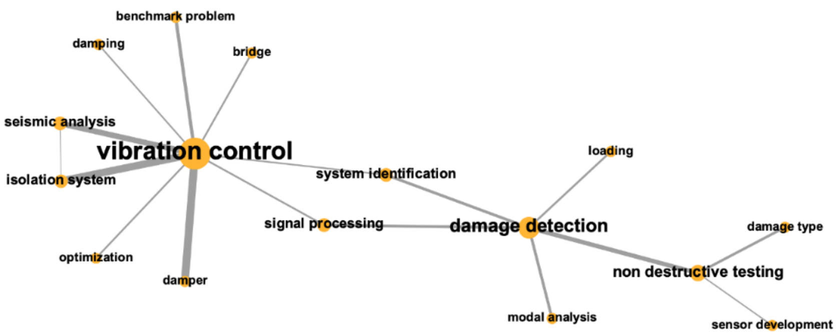


Fig. 5 Topic network for SHM research in Period 1 (2005–2009)

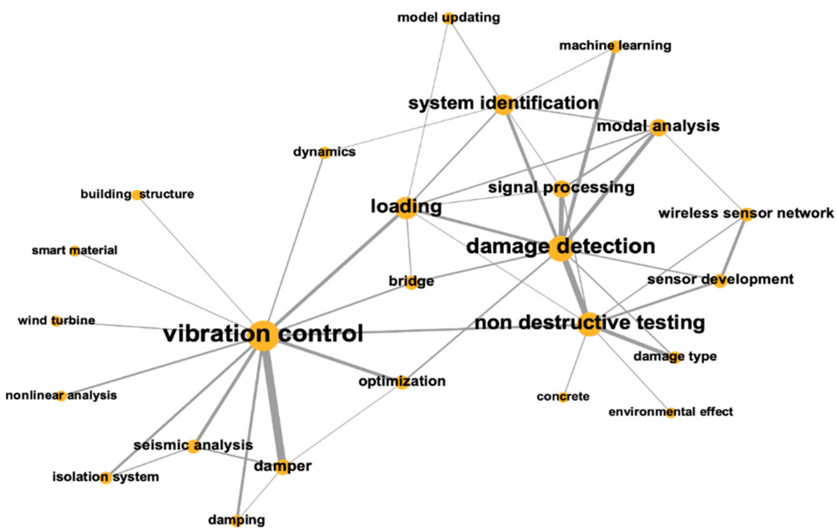


Fig. 6 Topic network for SHM research in Period 2 (2010–2014)

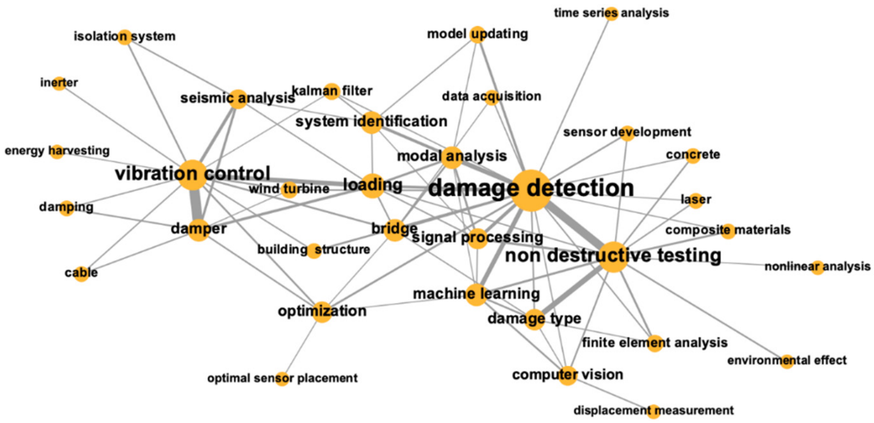


Fig. 7 Topic network for SHM research in Period 3 (2015–2019)

5.1 Research topic trends by quantitative aspects

Quantitative growth pattern of SHM field

The descriptive statistics indicate the quantitative growth in the SHM field, confirming the arguments of previous reviews (An *et al*. 2019, Fujino *et al*. 2019, Kim *et al*. 2016a, b, Spencer *et al*. 2019, Ye *et al*. 2019, Azimi *et al*. 2020). Considering the number of SHM-related publications and authors, Figs. 3 and 4 show that SHM studies have experienced quantitative growth. The number of publications increases from 22 in 2005 to 202 in 2013, i.e., approximately tenfold over eight years. As the three selected journals published more issues starting from 2013, this expanding trend is maintained through the year 2019, at which the yearly publication records become 495. The overall pattern of the quantitative changes in SHM-related authors is similar to the trends for the publications. The number of authors increases from 55 in 2005 to 570 in 2013. This record increases dramatically in 2019, by 1,570. This trend shows that the SHM field is actively growing, as new scholars are gradually becoming involved in this field. This quantitative expansion of the SHM field proves the increasing interest in implementing SHM systems in various real-world structures.

Dominant research topics

While the SHM field has expanded, several topics have been dominant for 15 years, as shown in Table 2. The constantly studied topics include *vibration control*, *damper*, *loading*, *damage detection*, and *non destructive testing*. These topics are closely related to each other, in that (1) vibration control aims to reduce the structural vibrations induced by external loading using a damper system (Jeong *et al*. 2019, Johnson *et al*. 2007), and (2) non-destructive testing is one of the widely adopted methods for damage detection (Hou and Xia 2020). Currently, machine learning and computer vision techniques have been utilized to detect structural damage based on non-destructive approaches (An *et al*. 2019, Spencer *et al*. 2019, Ye *et al*. 2019, Hou and Xia 2020, Azimi *et al*. 2020, Kim *et al*. 2019).

Topics in growth stage and mature stage.

Table 2 provides a hint for estimating the stage a topic is in the life cycle. First, the research subjects in the growth stage are *damage type*, *modal analysis*, and *data acquisition*. The ranking of *damage type* rises from the 14th in Period 1 to 7th in Period 3. A possible explanation for this rapid change is that researchers can detect various damage types by adopting state-of-the-art knowledge from other academic fields, such as machine learning, computer vision, and sensor-related technologies. Likewise, *modal analysis* shows a similar growth pattern; the scores for this topic are 31, 84, and 159 in each period, respectively. Advanced sensor devices, which can facilitate the measurement of in-service structural responses, are likely affecting the rise of this topic (An *et al*. 2019, Fujino *et al*. 2019, Kim *et al*. 2016a, b, Spencer *et al*. 2019, Ye *et al*. 2019, Hou and Xia 2020). The *data acquisition* topic supports the influence of advanced sensor technologies on measuring structural responses, in that this topic has shown a growth trend since Period 1.

The representative mature research topics are *system identification* and *smart material*. The *system identification* topic ranks 5th in Periods 1 and 2, with 49 and 86, respectively. Although the increasing pattern appears to hold in Period 3 with a score of 95, its growth rate decreases from 75.5% (from Period 1 to 2) to 10.5% (from Period 2 to 3). A similar trend can be observed for the *smart material*, which shows a decreasing growth rate with records of 28, 54, and 63 in Periods 1–3, respectively. This downturn in the growth rate reflects the maturity of these research topics.

Rise of new research topics

This study observes emerging topics such as *environmental effect*, *machine learning*, and *computer vision* within the top 20 topics, as shown in Table 2. The rise of new research topics shows clear evidence that scholars are attempting to solve SHM-related problems by adopting various new ideas from other research fields. For example, the topic of *environmental effect* emerges in the top 20 ranks for the first time in Period 3. As environmental factors, such as temperature and wind, can cause changes in structural dynamic properties (Hou and Xia 2020), numerous studies have considered environmental effects to evaluate structural health conditions, such as modal properties (Laory *et al*. 2014, Barsocchi *et al*. 2021) and damage severity (Hou and Xia 2020, Lee *et al*. 2020b, Ni *et* *al*. 2020).

New methodologies from other research fields have been introduced to address SHM-related issues in recent years. For example, *machine learning* has become an important research topic, as a data-driven approach to addressing SHM-related problems. The *machine learning* category comprises keywords such as artificial intelligence, machine learning, and deep learning. The *Machine learning* is the 16th most frequently mentioned topic in Period 2 but is ranked 8th in Period 3. This finding agrees with previous studies that have focused on diagnosing structural health conditions (Ye *et al*. 2019, Hou and Xia 2020, Azimi *et al*. 2020). Moreover, computer vision techniques have emerged as a promising tool for SHM studies, appearing within the top 20 ranks for the first time (15th rank) in Period 3.

5.2 Research topic trends by relational aspects

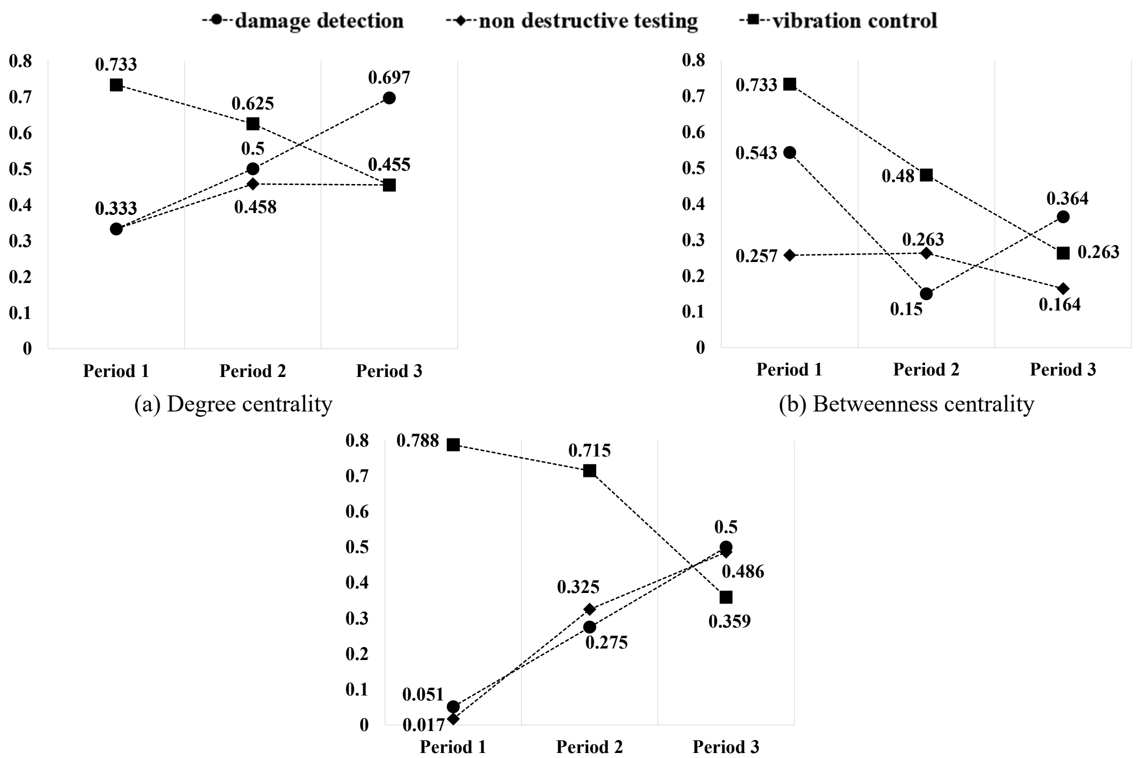
Impact change of dominant topics

Our descriptive analysis finds that several topics have received constant attention in the SHM. However, the topic networks provide another important insight into how the impacts of these dominant topics has changed over time, as shown in Fig. 8. First, this study observes that the overall impact of *vibration control* is reduced, and its bridging role shrinks. The degree centrality of *vibration control* in the three periods is 0.733, 0.625, and 0.455, respectively. The betweenness centrality scores also exhibit a decreasing pattern, with values of 0.733, 0.48, and 0.263 in Periods 1–3, respectively. The decreasing impact can be interpreted as an early sign that vibration control-related research is becoming mature. Second, the impact of *damage detection* increases, with degree centrality scores of 0.333, 0.5, and 0.697 in the three periods, respectively. This increasing pattern explains that the impact of *damage detection* is intensifying, and that more researchers have focused on this topic. As *non destructive testing* tends to appear together with *damage detection*, the overall impact of this topic has become strong in the topic networks as well.

Diversified research topics

The changes in the topic networks over the three periods show that research topics have diversified (Figs. 5-7). The network size (i.e., the number of nodes) and number of edges provide clear indications that SHM-related topics are complex. The size of the research topic network shows an increasing trend, that is 1,173, 2,425, and 4,906 in Periods 1–3, respectively. Every five years, the number of research topics doubled. In addition, the number of edges in all periods increases, i.e., from 4,126 in Period 1 to 8,840 in Period 2, and to 17,762 in Period 3. Considering the topics appearing with others more than eight times, the network sizes are 16, 25, and 34 in each period respectively, and the numbers of edges are 19, 53, and 87, respectively. This rapid growth of network size and number of linkages confirms that the research topics in the SHM field have been diversified for 15 years. These diversified research topics correspond well with those found in earlier SHM reviews (An *et al*. 2019, Fujino *et al*. 2019, Kim *et al*. 2016a, b, Spencer *et al*. 2019, Ye *et al*. 2019, Hou and Xia2020, Azimi *et al*. 2020).

Evidence of the diversification trend can be in the



(a) Degree centrality (b) Betweenness centrality

(c) Eigenvector centrality

Fig. 8 Centrality indices of three major topics in topic networks emergence of *machine learning* and *computer vision* in the topic network. SHM communities have attempted to adopt various new concepts from other academic fields, such as computer science, to solve SHM-related problems. The topic networks in Periods 2 and 3 indicate that *machine learning* has become one of the principal topics. The *machine learning* is included in the top 15 topics in the 2nd and 3rd topic networks (Figs. 6 and 7). The *computer vision* has become an important topic in interdisciplinary SHM studies, appearing for the first time in the Period 3 network. The degree centrality score of this topic is 0.212, showing that computer vision techniques have received significant interest from SHM scholars over the last five years.

Expansion of interdisciplinary research applications

The research topics co-occurring with *machine learning* and *computer vision* have expanded. In Period 2, *damage detection* and *system identification* are the two major co-appearing topics with *machine learning* (Fig. 6). The popularity of *machine learning* increases in Period 3, with various co-appearing topics such as *damage detection*, *non destructive testing*, *computer vision*, *damage type*, *modal analysis*, *signal processing*, and *optimization* (Fig. 7). The co-occurrence between *machine learning* and others corresponds to previous studies presenting application examples, such as those for damage detection (Ye *et al.* 2019, Hou and Xia 2020, Azimi *et al.* 2020), modal analysis (Ye *et al.* 2019, Azimi *et al.* 2020, Kim and Sim 2019), condition assessment (Ye *et al.* 2019, Azimi *et al.* 2020, Jeong *et al.* 2020), and signal processing (Ye *et al.* 2019, Azimi *et al.* 2020).

The topic networks show that *computer vision* is broadly studied along with topics such as *displacement measurement*, *non destructive testing*, and *damage detection*. Computer vision-based SHM has been applied for inspection (e.g., component recognition and damage detection) and monitoring purposes (e.g., measurement of structural responses) (Spencer *et al.* 2019). For example, the linkage between computer vision and displacement measurement shows that one recent trend in SHM research is to apply computer vision techniques to measure the displacements of structures (Lee *et al.* 2012, 2017, 2019, 2020a, Park *et al.* 2016, Fukuda *et al.* 2010, Lee and Shinozuka 2006). The co-occurrence between *computer vision* and *non destructive testing* is in agreement with previous studies indicating that computer vision techniques can provide efficient non-destructive methods for assessing structural conditions (Spencer *et al.* 2019). Furthermore, the development of machine learning techniques is known to act as a trigger for enabling the wide application of computer vision tools to SHM studies (Spencer *et al.* 2019, Ye *et al.* 2019), which can be found in the linkage between *computer vision* and *machine learning*.

6. Conclusions

This study proposes a framework tailored to analyzing the overall research topic trends in SHM by applying a bibliometric analysis. This is the first study to report a framework designed to understand the development history of the SHM field in the context of both the quantitative and relational changes in the principal research topics. We define quantitative-based research trends as changes in the occurrences of entities that the scientific papers contain, such as in the number of publications and authors or the spotlighted research topics. The relationship-based research trends reflect changes in the emerging research topics based on a network analysis. As the first framework designed to identify overall research trends, this study applies the proposed framework to study SHM for the first time to analyze the research topic trends; this has not been realized in previous SHM reviews (An *et al.* 2019, Fujino *et al.* 2019, Kim *et al.* 2016a, b, Spencer *et al.* 2019, Ye *et al.* 2019, Hou and Xia 2020, Azimi *et al.* 2020).

As a fundamental study proposing a framework for analyzing research trends, the results herein have several noteworthy contributions to SHM studies, as well as in other academic fields. First, the proposed framework allows us to identify the footprint of SHM research topics by analyzing their quantitative and relational changes, which have not been covered by general review papers (An *et al.* 2019, Fujino *et al.* 2019, Kim *et al.* 2016a, b, Spencer *et al.* 2019, Ye *et al.* 2019, Hou and Xia 2020, Azimi *et al.* 2020). Tracking the relational patterns in topic networks, in particular, provides deeper insights for understanding research trends, for example, SHM topics have become diversified and interdisciplinary by the active adoption of state-of-the-art technologies from other fields. Second, this work provides clear explanations regarding the diversification of research subjects in the SHM field. Topic networks visualize the phenomenon of diversified research topics, as well as spotlighted research topics. Third, the proposed framework can provide consistent insights at the macroscopic level of SHM research trends. By analyzing the bibliographic data, it is possible to obtain empirical evidence for changes in the spotlighted research topics in overall SHM studies. Furthermore, the framework can be used to conduct a comprehensive review of the SHM field through objective information collected by online search engines with less time and cost. Finally, the proposed method contributes to existing knowledge for capturing research topic trends based on bibliometric-based methodological validations. The framework may be applied to other research fields universally to understand their research topic trends, thereby enlightening the direction of scientific research.

Acknowledgments

This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2020R1A2C2014797) and an R&D Program (PK2203B1) of the Korea Railroad Research Institute, Korea.

References

Abudayyeh, O., Dibert-DeYoung, A. and Jaselskis, E. (2004), "Analysis of trends in construction research: 1985–2002", *J.*

Constr. *Eng*. *Manag*., **130**(3), 433-439. https://doi.org/10.1061/(ASCE)0733-9364(2004)130:3(433)

An, Y., Chatzi, E., Sim, S.H., Laflamme, S., Blachowski, B. and Ou, J. (2019), "Recent progress and future trends on damage identification methods for bridge structures", *Struct*. *Control Health Monitor*., **26**(10), e2416. https://doi.org/10.1002/stc.2416

Azimi, M., Eslamlou, A.D. and Pekcan, G. (2020), "Data-driven structural health monitoring and damage detection through deep learning: State-of-the-art review", *Sensors-Basel*, **20**(10), 2778. https://doi.org/10.3390/s20102778

Barsocchi, P., Bartoli, G., Betti, M., Girardi, M., Mammolito, S., Pellegrini, D. and Zini, G. (2021), "Wireless sensor networks for continuous structural health monitoring of historic masonry towers", *Int*. *J*. *Archit*. *Herit*., **15**(1), 22-44. https://doi.org/10.1080/15583058.2020.1719229

Borgatti, S.P. (2005), "Centrality and network flow", *Soc*. *Networks*, **27**(1), 55-71. https://doi.org/10.1016/j.socnet.2004.11.008

Chang, Y.W. and Huang, M.H. (2012), "A study of the evolution of interdisciplinarity in library and information science: Using three bibliometric methods", *J*. *Am*. *Soc*. *Inf*. *Sci*. *Tec*., **63**(1), 22-33. https://doi.org/10.1002/asi.21649

Demiroz, F. and Haase, T.W. (2019), "The concept of resilience: a bibliometric analysis of the emergency and disaster management literature", *Local Gov*. *Stud*., **45**(3), 308-327. https://doi.org/10.1080/03003930.2018.1541796

Ferreira, M.P., Santos, J.C., de Almeida, M.I.R. and Reis, N.R. (2014), "Mergers & acquisitions research: A bibliometric study of top strategy and international business journals, 1980–2010", *J*. *Bus*. *Res*., **67**(12), 2550-2558. https://doi.org/10.1016/j.jbusres.2014.03.015

Freeman, L.C., Roeder, D. and Mulholland, R.R. (1979), "Centrality in social networks: II. Experimental results", *Soc*. *Networks*, **2**(2), 119-141. https://doi.org/10.1016/0378-8733(79)90002-9

Fujino, Y., Siringoringo, D.M., Ikeda, Y., Nagayama, T. and Mizutani, T. (2019), "Research and implementations of structural monitoring for bridges and buildings in Japan", *Engineering*, **5**(6), 1093-1119. https://doi.org/10.1016/j.eng.2019.09.006

Fukuda, Y., Feng, M.Q. and Shinozuka, M. (2010), "Cost-effective vision-based system for monitoring dynamic response of civil engineering structures", *Struct*. *Control Health Monitor*., **17**(8), 918-936. https://doi.org/10.1002/stc.360

Hong, Y., Chan, D.W., Chan, A.P. and Yeung, J.F. (2012), "Critical analysis of partnering research trend in construction journals", *J*. *Manage*. *Eng*., **28**(2), 82-95. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000084

Hou, R. and Xia, Y. (2020), "Review on the new development of vibration-based damage identification for civil engineering structures: 2010–2019", *J*. *Sound Vib*., 115741. https://doi.org/10.1016/j.jsv.2020.115741

Jeong, S., Lee, J., Cho, S. and Sim, S.H. (2019), "Integrated cable vibration control system using Arduino", *Smart Struct*. *Syst*., *Int*. *J*., **23**(6), 695-702. https://doi.org/10.12989/sss.2019.23.6.695

Jeong, S., Kim, H., Lee, J. and Sim, S.H. (2020), "Automated wireless monitoring system for cable tension forces using deep learning", *Struct*. *Health Monitor*., 1475921720935837. https://doi.org/10.1177/1475921720935837

Johnson, E.A., Baker, G.A., Spencer Jr, B.F. and Fujino, Y. (2007), "Semiactive damping of stay cables", *J*. *Eng*. *Mech*., **133**(1), 1-11. https://doi.org/10.1061/(ASCE)0733-9399(2007)133:1(1)

Ke, Y., Wang, S., Chan, A.P. and Cheung, E. (2009), "Research trend of public-private partnership in construction journals", *J*. *Constr*. *Eng*. *M*., **135**(10), 1076-1086. https://doi.org/10.1061/(ASCE)0733-9364(2009)135:10(1076)

Khan, A., Choudhury, N., Uddin, S., Hossain, L. and Baur, L.A. (2016), "Longitudinal trends in global obesity research and collaboration: a review using bibliometric metadata", *Obes*. *Rev*., **17**(4), 377-385. https://doi.org/10.1111/obr.12372

Kim, H. and Sim, S.H. (2019), "Automated peak picking using region-based convolutional neural network for operational modal analysis", *Struct*. *Control Health Monitor*., **26**(11), e2436. https://doi.org/10.1002/stc.2436

Kim, R.E., Moreu, F. and Spencer Jr, B.F. (2015), "System identification of an in-service railroad bridge using wireless smart sensors", *Smart Struct*. *Syst*., *Int*. *J*., **15**(3), 683-698. https://doi.org/10.12989/sss.2015.15.3.683

Kim, J., Lee, S., Shim, W. and Kang, J. (2016a), "A mapping of marine biodiversity research trends and collaboration in the east Asia region from 1996–2015", *Sustainability*, **8**(10), 1075. https://doi.org/10.3390/su8101075

Kim, J.T., Sim, S.H., Cho, S., Yun, C.B. and Min, J. (2016b), "Recent R&D activities on structural health monitoring in Korea", *Struct*. *Monitor*. *Maint*., *Int*. *J*., **3**(1), 91-114. https://doi.org/10.12989/smm.2016.3.1.091

Kim, B.J., Park, H.G. and Chung, J.B. (2017), "Social network analysis of the Korean disaster-safety industry", *Disaster Prev*. *Manag*., **27**, 28-42. https://doi.org/10.1108/DPM-08-2017-0212

Kim, H., Ahn, E., Shin, M. and Sim, S.H. (2019), "Crack and noncrack classification from concrete surface images using machine learning", *Struct*. *Health Monitor*., **18**(3), 725-738. https://doi.org/10.1177/1475921718768747

Kim, B.J., Jeong, S. and Chung, J.B. (2021), "Research trends in vulnerability studies from 2000 to 2019: Findings from a bibliometric analysis", *Int*. *J*. *Disast*. *Risk Re*., **56**, 102141. https://doi.org/10.1016/j.ijdrr.2021.102141

Laory, I., Trinh, T.N., Smith, I.F. and Brownjohn, J.M. (2014), "Methodologies for predicting natural frequency variation of a suspension bridge", *Eng*. *Struct*., **80**, 211-221. https://doi.org/10.1016/j.engstruct.2014.09.001

Lee, C.J. (2012), "A Kuhnian critique of psychometric research on peer review", *Philos*. *Sci*., **79**(5), 859-870. https://doi.org/10.1086/667841

Lee, J.J. and Shinozuka, M. (2006), "A vision-based system for remote sensing of bridge displacement", *Ndt&E Int*., **39**(5), 425-431. https://doi.org/10.1016/j.ndteint.2005.12.003

Lee, J.H., Ho, H.N., Shinozuka, M. and Lee, J.J. (2012), "An advanced vision-based system for real-time displacement measurement of high-rise buildings", *Smart Mater*. *Struct*., **21**(12), 125019. https://doi.org/10.1088/0964-1726/21/12/125019

Lee, J., Lee, K.C., Cho, S. and Sim, S.H. (2017), "Computer vision-based structural displacement measurement robust to light-induced image degradation for in-service bridges", *Sensors*, **17**(10), 2317. https://doi.org/10.3390/s17102317

Lee, J., Lee, K.C., Lee, S., Lee, Y.J. and Sim, S.H. (2019), "Long-term displacement measurement of bridges using a LiDAR system", *Struct*. *Control Health Monitor*., **26**(10), e2428. https://doi.org/10.1002/stc.2428

Lee, J., Lee, K.C., Jeong, S., Lee, Y.J. and Sim, S.H. (2020a), "Long-term displacement measurement of full-scale bridges using camera ego-motion compensation", *Mech*. *Syst*. *Signal Pr*., **140**, 106651. https://doi.org/10.1016/j.ymssp.2020.106651

Lee, K., Jeong, S., Sim, S.H. and Shin, D.H. (2020b), "Field experiment on a PSC-I bridge for convolutional autoencoder-based damage detection", *Struct*. *Health Monitor*., **20**(4), 1627-1643. https://doi.org/10.1177/1475921720926267

Moreu, F., Li, J., Jo, H., Kim, R.E., Scola, S., Spencer Jr, B.F. and LaFave, J.M. (2016), "Reference-free displacements for condition assessment of timber railroad bridges", *J*. *Bridge Eng*., **21**(2), 04015052. https://doi.org/10.1061/(ASCE)BE.1943-5592.0000805

Newman, M.E. (2016), "Mathematics of networks", In: *The New Palgrave Dictionary of Economics*, pp. 1-8, Springer.

Ni, Y.Q., Wang, Y.W. and Zhang, C. (2020), "A Bayesian approach for condition assessment and damage alarm of bridge expansion joints using long-term structural health monitoring data", *Eng. Struct.*, **212**, 110520. https://doi.org/10.1016/j.engstruct.2020.110520

Oraee, M., Hosseini, M.R., Papadonikolaki, E., Palliyaguru, R. and Arashpour, M. (2017), "Collaboration in BIM-based construction networks: A bibliometric-qualitative literature review", *Int. J. Proj. Manag.*, **35**(7), 1288-1301. https://doi.org/10.1016/j.ijproman.2017.07.001

Palmer, A.L., Sese, A. and Montano, J.J. (2005), "Tourism and statistics: Bibliometric study 1998–2002", *Ann. Tourism Res.*, **32**(1), 167-178. https://doi.org/10.1016/j.annals.2004.06.003

Park, C., Ho, H.N., Jo, B.W. and Lee, J.J. (2016), "An efficient vision-based three-dimensional motion measurement system for civil infra-structures", *Exp. Techniques*, **40**(2), 629-637. https://doi.org/10.1007/s40799-016-0066-0

Rosas, S.R., Kagan, J.M., Schouten, J.T., Slack, P.A. and Trochim, W.M. (2011), "Evaluating research and impact: a bibliometric analysis of research by the NIH/NIAID HIV/AIDS clinical trials networks", *PloS One*, **6**(3), e17428. https://doi.org/10.1371/journal.pone.0017428

Schlederer, M., Mueller, K.M., Haybaeck, J., Heider, S., Huttary, N., Rosner, M., Hengstschlager, M., Moriggl, R., Dolznig, H. and Kenner, L. (2014), "Reliable quantification of protein expression and cellular localization in histological sections", *PloS One*, **9**(7), e100822. https://doi.org/10.1371/journal.pone.0100822

Sim, S.H. (2016), "Estimation of flexibility matrix of beam structures using multisensor fusion", *J. Struct. Integrity Maint.*, **1**(2), 60-64. https://doi.org/10.1080/24705314.2016.1179494

Spencer Jr, B.F., Hoskere, V. and Narazaki, Y. (2019), "Advances in computer vision-based civil infrastructure inspection and monitoring", *Engineering*, **5**(2), 199-222. https://doi.org/10.1016/j.eng.2018.11.030

Uddin, S., Hossain, L., Abbasi, A. and Rasmussen, K. (2012), "Trend and efficiency analysis of co-authorship network", *Scientometrics*, **90**(2), 687-699. https://doi.org/10.1007/s11192-011-0511-x

Ugolini, D., Puntoni, R., Perera, F.P., Schulte, P.A. and Bonassi, S. (2007), "A bibliometric analysis of scientific production in cancer molecular epidemiology", *Carcinogenesis*, **28**(8), 1774-1779. https://doi.org/10.1093/carcin/bgm129

Uysal, Ö.Ö. (2010), "Business ethics research with an accounting focus: A bibliometric analysis from 1988 to 2007", *J. Bus. Ethics*, **93**(1), 137-160. https://doi.org/10.1007/s10551-009-0187-9

Woo, S.H., Kang, D.J. and Martin, S. (2013), "Seaport research: An analysis of research collaboration using Social Network Analysis", *Transport Rev.*, **33**(4), 460-475. https://doi.org/10.1080/01441647.2013.786766

Ye, Q., Li, T. and Law, R. (2013), "A coauthorship network analysis of tourism and hospitality research collaboration", *J. Hosp. Tour. Res.*, **37**(1), 51-76. https://doi.org/10.1177/1096348011425500

Ye, X.W., Jin, T. and Yun, C.B. (2019), "A review on deep learning-based structural health monitoring of civil infrastructures", *Smart Struct. Syst., Int. J.*, **24**(5), 567-586. https://doi.org/10.12989/sss.2019.24.5.567

Zhai, X., Li, Z., Gao, K., Huang, Y., Lin, L. and Wang, L. (2015), "Research status and trend analysis of global biomedical text mining studies in recent 10 years", *Scientometrics*, **105**(1), 509-523. https://doi.org/10.1007/s11192-015-1700-9